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Early warning method for the commodity prices based on artificial neural networks: SMEs case

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Abstract

Applications based on Artificial Neural Networks (ANN) have been developed thanks to the advance of the technological progress which has permitted the development of sales forecasting on consumer products, improving the accuracy of traditional forecasting systems. The present study compares the performance of traditional models against other more developed systems such as ANN, and Support Vector Machines or Support Vector Regression (SVM-SVR) machines. It demonstrates the importance of considering external factors such as macroeconomic and microeconomic indicators, like the prices of related products, which affect the level of sales in an organization. The data was collected from a group of supermarkets belonging to the SMEs sector in Colombia. At first, a pre-processing was carried out to clean, adapt and standardize data bases. Then, since there was no labeled information about the pairs of substitute or complementary products, it was necessary to implement a cross-elasticity analysis. In addition, a harmonic average (f1-score) was considered at several points to establish priorities in some products and obtained results. The model proposed in this study shows its potential application in the product sales forecasting with high rotation in SMEs supermarkets since their results are more accurate than those obtained using traditional procedures.

Keywords: *predictive model, multilayer Perceptron, Multiple Input Multiple Output, forecast, support vector machines, cyclic variation.*

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1. Introduction

The business world is driven by the demand for products and services that customers require. However, the patterns of demand considerably vary from one period to another. Currently, all company plans face the uncertainty that arises in the environment where it is located. These plans are used as a guide to determine resources needed to cover the expected demand (Sanclemente, J; 2007)[1]. In the context of the inventory management, it is well known that organizations define a safety stock that allows them to respond to changes in demand and the delay in the delivery of new orders. This measure is necessary to avoid the inventory deficit which represents losses on sales, and a bad image in the eyes of consumers, and is essential for facing the growing competition in most of the business sectors (Amelec, V and Alexander, P; 2015)[2], (Ayala, S; 2015)[3].

Due to the non-linear behavior of sales, there is a high level of uncertainty in the formulation of forecasts in many companies. The production planning begins by establishing the necessary amount of finished product to produce or maintain a stock for a time period. This planning determines the level of sales that the company could have, considering factors such as: skills, abilities, attitudes, and behaviors of the population (Atsalakis, G and Valavanis, K; 2015) [4]. However, the forecast models known up to the present provide results with a certain error degree. The present study compares the performance of traditional models against the more developed systems such as Artificial Neural Networks (ANN) and Support Vector Machines or Support Vector Regression (SVM-SVR) machines, for forecasting the demand of the main products in the supermarkets at the SMEs sector in Colombia, considering the micro- and macro-economic factors in this country.

The expectation is that these new approaches significantly decrease the error generated by the traditional forecasts. There is a significant volume of reported experiences indicating the effectiveness of the ANN models for time-series forecasting, including the electricity price forecast (Matich, D; 2001) [5], series of European industrial production and econometric forecasting models (Viloria, A and Robayo, P. 2016) [6].

2. Literature Review

There are traditional models that are probabilistic, deterministic, and hybrids, such as: Simple Moving Average, Weighted Moving Average, Exponential Smoothing, Regression Analysis, Box-Jenkins method (ARIMA), trend projections, and other, used to generate forecasts providing certain advantages and disadvantages when compared to the other models. However, these traditional models are unable to offer good results in the current environment of high uncertainty and constant changes. For this reason, it is necessary to adopt new paradigms based on numeric modeling of nonlinear systems, like the Artificial Neural Networks (ANN), and the Support Vector Regression (SVR) (Zhang, G; 2003) [7].

The ANNs have shown a considerable development for reducing the error compared to traditional forecasting models. The difference lies in the fact that these new methods for analyzing indicators is based on the artificial learning, meaning that this algorithm acquires experience through the historical records that are entered as input values (Toro, E. et al; 2004) [8]. The demand for a product is generated by the interaction of several factors which are too complex to describe accurately with a mathematical model. So, this study proposes the use of the demand forecast.

In present times, thanks to various research groups of several universities worldwide, the ANNs have reached an acceptable maturity level and permit a number of applications including (Vitez, O; 2017) [9]:

- Pattern recognition, voice and video, image compression.
- Study and prediction of very complex events like the stock market.

- Support applications for medicine in all kinds of applications requiring the analysis of large amounts of data, etc.

Another method to achieve good results is the Support Vector Regression (SVR) which provides greater accuracy and improves the optimum global measure. Initially, the Support Vector Machines (SVM) were implemented for pattern recognition and classification (Wu, Q. et a; 2008)[10], but currently, SVM has been implemented for linear regression (SVR). As examples of experiences with this method, (Sapankevych, N and Sankar, R; 2009)[11] used this system to forecast sales of consumer products such as cars and perishable agricultural commodities respectively.

The use of more developed systems, such as ANN and Support Vector Machines have presented great improvements in forecasting as technology and more complex data management systems have evolved. An extensive review of scientific publications applying ANN on the price forecasting in the stock market around the world is exhibited by Villada, F. et al. (2012)[12] this study concludes that the deep learning methods, compared to conventional models, show better results when increasing its accuracy considerably. However, they emphasize that these models present a difficulty in their structural conception because most cases are the result of a trial and error experimentation. In contrast, Ruan, D (2013)[13] confronted the resulting performance in time-series and diffuse logic with a structure based on time series, changing the inputs to the price variation and the trend sign, concluding that the stock market index of Taiwan provided more accurate results than the traditional forecasting models.

3. Data and Methods

In this study, the raw data were obtained from the National Administrative Department of Statistics of Colombia (DANE - Departamento Administrativo Nacional de Estadísticas), which provided a sales database of 2353 supermarkets belonging to the SMEs sector in the main capitals of Colombia in the time period from 2014 to 2017 (Lis-Gutiérrez J. et al; 2018)[14]. The macroeconomic variables considered in this study range from food inflation, GDP, employment rate, minimum wage to commercial balance and capital flow of the nation. Internal factors such as demand, and substitute and complementary products were also analyzed.

The used method is summarized as follows. For the selection of products, an order is emitted according to the f1-score harmonic average (Viloria, A and Gaitan-Angulo, M; 2016)[15], which is defined as the reciprocal of the arithmetic mean of the reciprocals. This value is used to determine the average of variations with respect to time. It is mostly used to find the average values of efficiency and error. This study allows to obtain a factor considering that both sales and quantity are important. In total, 10 products were selected.

With the sample of products to be considered, the interactivity with other products is analyzed to select the substitutes and complementary products. A quantitative alternative for selecting substitute and complementary products is the cross-elasticity of demand, which analyzes two products and, according to their sign, establishes whether it is substitute (+) or complementary (-). Then, the resulting maximum or minimum value represents greater interaction between both products, that is, the maximum positive value is chosen for substitute, and the maximum negative value for complementary. Cross-elasticity is defined as the proportional variation in the demanded quantity for a good or service caused by a proportional variation in the price of other goods (Garcia, M; 2003)[16].

To permit the comparison of the different methods and their effectiveness, it is necessary to take them to a single scale. For this purpose, the average absolute percentage error is calculated.

The Garson's algorithm for determining the level of importance was developed to determine the degree or level of importance of an input indicator in ANN. In many cases related to the measurement of the variables, the weights in the hidden layer and their interactions in the output network are considered. A measure proposed by Hanke, J and Wichern, D (2006)[17] consists of dividing the weights of the hidden layer into components linked to each input node and then assigning each of them a percentage of the total weights.

4. Results and Discussions

To select the products on which the forecasts were made, the f1-score criterion is used. The ordering by this factor considered both the quantity and the value of sales for the selection of the most important products. Table 1 presents the values of the f1-score factor for each selected product.

Table 1. *Prioritization and selection of products*

Code	Line	Category	Quantity	F1-SCORE
P1	Birds	Chicken	87318	121939.957
P2	Groceries	Sugar	57785	65264.5132
P3	Birds	Eggs	64679	62848.756
P4	Groceries	Noodles and pasta	66609	50443.7233
P5	Liquors	Beer	52489	46963.3935
P6	Dairy products	Milk	49960	40689.3872
P7	Groceries	Salt	46920	33567.0352
P8	Cleaning	Washed	36773	31722.393
P9	Groceries	Tuna	25126	31206.8012
P10	Groceries	Oil	27232	28903.9777

Table 2 shows the results obtained, including the mean absolute percentage error (MAPE). The results were obtained from 600 repetitions of ANN training. The method used requires that one part of data be for training and another for testing, so an 80/20 ratio was chosen over the total data (Obando, J. 2000)[18].

Table 2. Comparison of general results

Product	P1	P2	P3	P4	P5	P6	P7	P8 (sin I5)	P9	P10	Mape Promotion/ Average
Simple moving average (3)	8.74%	9.73%	7.30%	8.10%	42.43%	7.57%	6.96%	9.79%	4.13%	12.20%	11.70%
Weighted moving average	10.10%	9.77%	9.22%	9.69%	34.55%	9.51%	7.08%	8.71%	6.24%	16.58%	12.15%
Smoothing simple exponential	7.84%	9.21%	6.36%	8.48%	50.06%	7.38%	5.67%	9.03%	9.28%	12.01%	12.53%
Linear regression	10.98%	25.26%	12.78%	12.52%	33.83%	10.94%	9.79%	28.95%	9.53%	20.04%	17.46%
Seasonal or cyclical variation	23.49%	32.74%	27.48%	26.39%	38.33%	29.39%	31.64%	68.06%	64.44%	73.45%	41.54%
Box-Jenkins - ARIMA (1,0,0)	8.52%	9.57%	7.95%	8.23%	52.57%	6.58%	7.79%	12.01%	6.45%	10.87%	13.05%
ANN	7.01%	13.62%	10.83%	8.08%	21.37%	7.31%	6.20%	10.53%	7.87%	9.57%	10.24%
(SVR) Support Vector Regression	11.41%	16.37%	5.96%	11.26%	26.11%	13.44%	8.25%	6.52%	10.81%	18.15%	12.83%

The analyses carried out permit to observe that the best average value of MAPE in Table 2 is of ANN with 10.24%. This value is significantly different from other traditional forecasting models. This result allows to synthesize that there may be a level of adjustment in the training case and in the increase of information to adjust the model already trained, which is a probable hypothesis if there is not an optimal amount of training examples to reach lower error levels. As can be seen in Table 2, the ANN model, compared to other more traditional forecasting models, present a considerably smaller error (Ayala, S. 2015)[3].

Product 2 (Fig. 1) and product 5 (Fig. 2) were selected to best exemplify the results obtained. The product 2 because it clearly shows a low variation period to period, and on the contrary, the product 5 reflects a high variation.

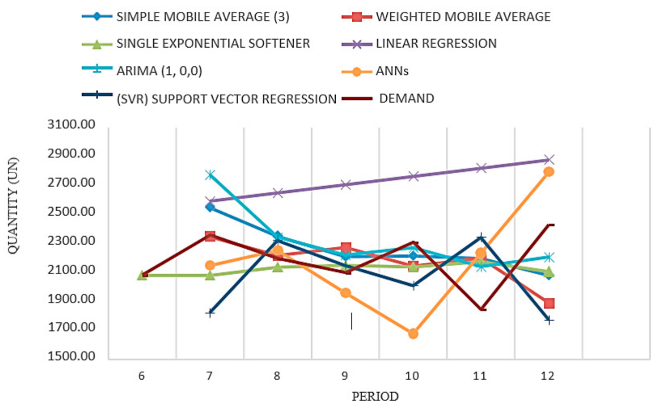

Fig 1. Product forecast comparison 2

Fig.1 and Fig. 2 show the comparison obtained between all the considered forecasts, but this result later varied in both graphs, that is, in Fig.1, due to the linear regression adjustment, there is an increasing trend with little variability from period to period. On the contrary, the same growing trend can be observed in Fig. 2, but with a much more marked variability from period to period. According to the results in Table 7, both products obtained different error values in ANN. In the case of product 2, the ANN was not sufficiently accurate and other forecast models were better adjusted, while in product 5, the ANN was very accurate and more adjusted than other forecasting models.

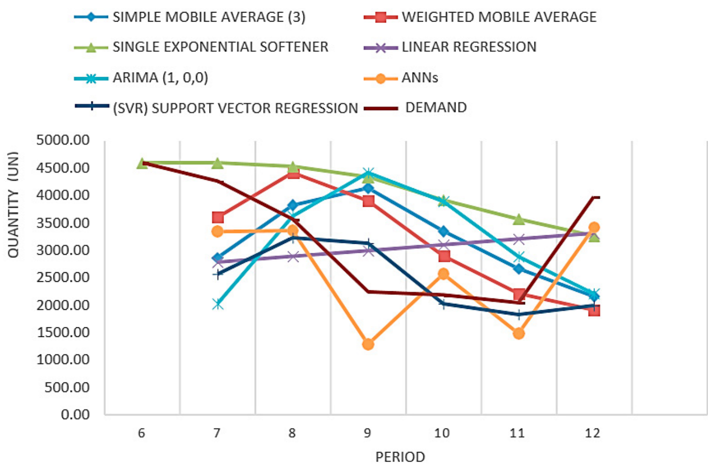

Fig. 2. Product forecast comparison 5

5. Conclusions

The analysis presented in this study highlights the effectiveness of using ANN for forecasting time series considering both external and internal factors of the organization. The effectiveness of the model could be verified obtaining better results compared to the traditional models. In addition, the use of more developed systems must be taken into account to anticipate the increasing demand for a product since organizations need to keep at the forefront of technology using more accurate forecasting models.

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